Introduction of
Machine Learning Security

Lecture 01

Overview of Machine Learning and Its Security

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Agenda

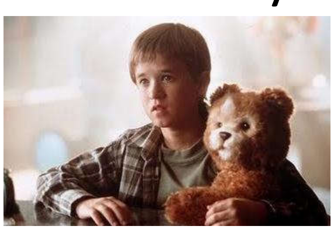
- Machine Learning Age
- Examples of Machine Learning Security
- Type of Attacks
- Adversary's Characteristics
- Refresher on Machine Learning

Machine Learning Age

- It will be great if a machine can learn by itself

Machine Learning Age

- Before, AI & ML mainly can be found in fictions or Hollywood Movies



Artificial Intelligence

Avengers: Age of Ultrons

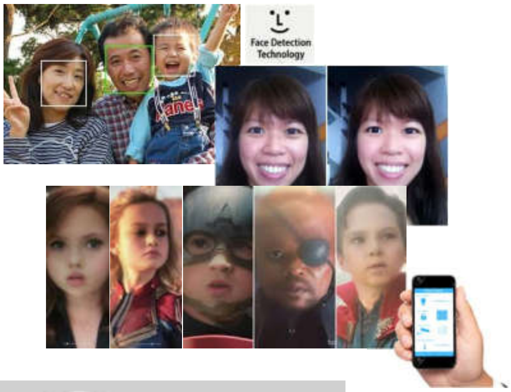
The Terminator

Alita: Battle Angel

iRobot

Machine Learning Age

- AI & ML is everywhere now!



AI Impact

AlphaGo
(2017)

Sedol Lee
(4 – 1)

Ke Jie
(3 – 0)

DeepMind

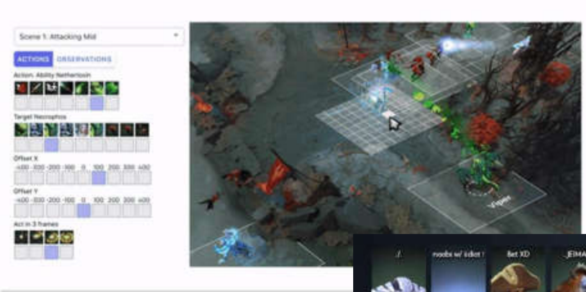
AlphaGo Zero
without using data from human games,
and stronger than any previous version

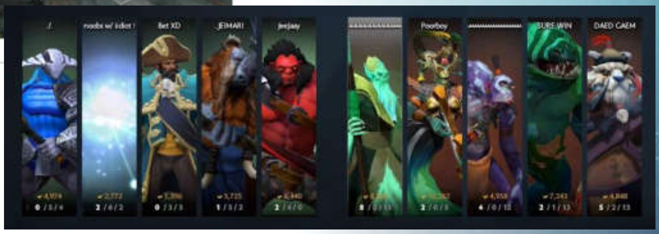
https://en.wikipedia.org/wiki/AlphaGo
https://deepmind.com/

AI Impact

OpenAI Five (2018)
Dota 2 Bot

Defeat the professional team twice
99.4% win in 42,729 matches with public players





OpenAI

https://en.wikipedia.org/wiki/OpenAI_Five

AI Impact

IBM: Project Debater (2019)

“We should subsidize preschool.”
- Project Debater (Agree)
- Harish Natarajan (Disagree)

15 mins Preparation
4 mins Opening statement
4 mins Rebuttal
2 mins Summary

58%: Project Debater better enriched their knowledge about the topic compared to Harish’s 20%

Poll	Agree	Disagree	Undecided
Before	79%	13%	8%
After	62% (-17%)	30% (+17%)	8%

https://www.research.ibm.com/artificial-intelligence/project-debater/live/

AI Impact

OpenAI: ChatGPT (2022)

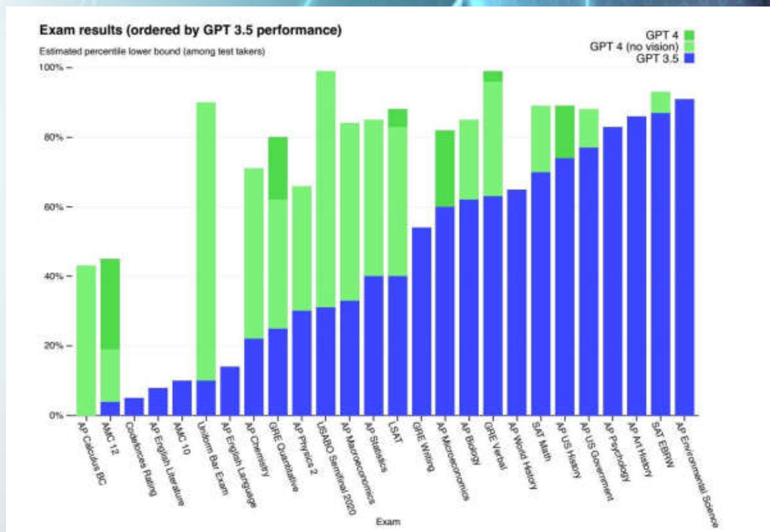
- Chat with images, voice and create images
- Understanding: Summary, extraction, expansion
- Translation
- Programming

Large Language Model

Replace the equivalent of 300 million full-time jobs

"ChatGPT is scary good, we are not far from dangerously strong AI.“ by Elon Musk

OpenAI



https://openai.com/chatgpt

AI Impact

OpenAI: Sora (2024)

- Create realistic and imaginative scenes from text instructions

A stylish woman walks down a Tokyo street filled with warm glowing neon and animated city signage. She wears a black leather jacket, a long red dress, and black boots, and carries a black purse. She wears sunglasses and red lipstick. She walks confidently and casually. The street is damp and reflective, creating a mirror effect of the colorful lights. Many pedestrians walk about.

OpenAI

https://openai.com/sora

AI Impact

https://openai.com/sora

AI Impact

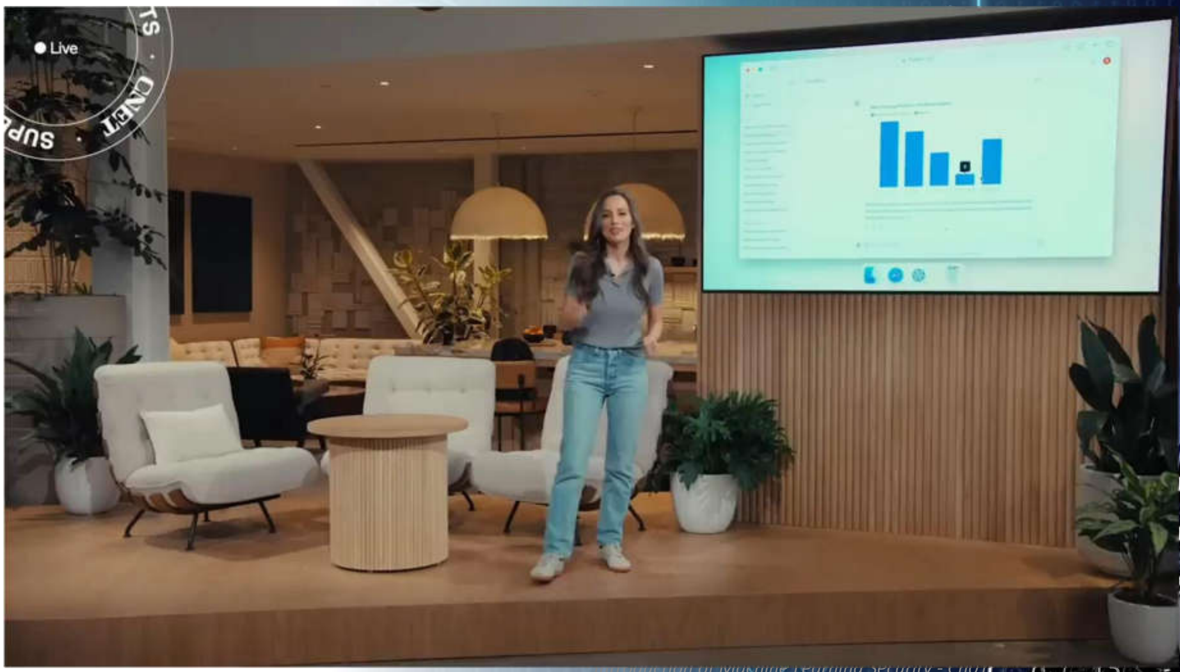
Historical footage of California during the gold rush

A close up view of a glass sphere that has a zen garden within it. There is a small dwarf in the sphere who is raking the zen garden and creating patterns in the sand.

https://openai.com/sora

AI Impact

OpenAI ChatGPT 4o



OpenAI

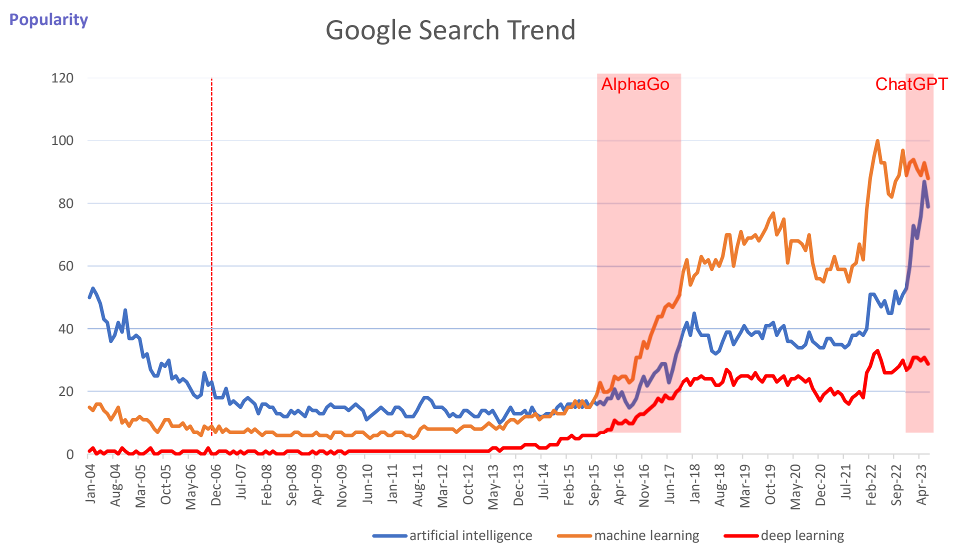
https://openai.com/sora

AI Impact

https://openai.com/sora

Machine Learning Age

- Due to the great success of Deep Learning, Machine Learning becomes more popular

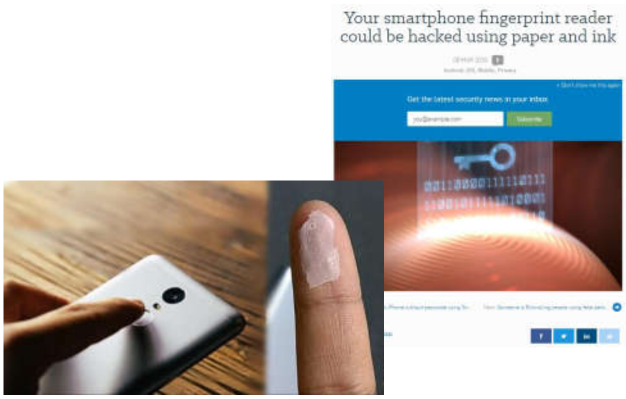


Machine Learning Age

- Everything looks good?!?

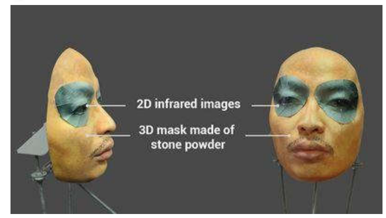
Machine Learning: Security

- Person Identification in Mobile
  - Fingerprint
  - Face (RGB, Depth, Inferred)




bdnews24.com

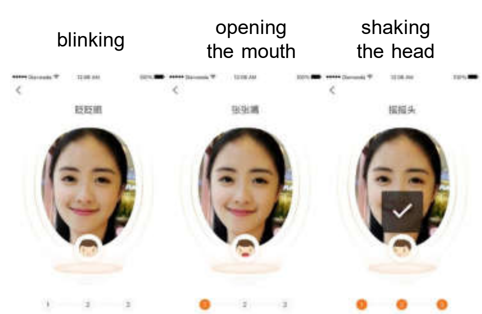
Vietnamese researcher shows iPhone X face ID "hack"



https://nakedsecurity.sophos.com/2016/03/08/your-smartphone-fingerprint-reader-could-be-hacked-using-paper-and-ink/
https://www.reuters.com/article/us-apple-vietnam-hack-id

Machine Learning: Security

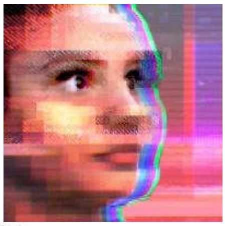
- Action videos showing movements such as shaking heads, blinking, and opening the mouth by using High-Definition Headshots (March 2021, Shanghai)
- Fool the liveness detection of person identification



https://m.huanqiu.com/article/42WIa03j3I9

Machine Learning: Security

- **Tay** is a chatter bot released by Microsoft via Twitter in 2016
- Learn from interacting with human users of Twitter
- 16 hours after releasing, Tay was shut down due to her abusive and offensive messages



https://en.wikipedia.org/wiki/Tay_(bot)

Machine Learning: Security

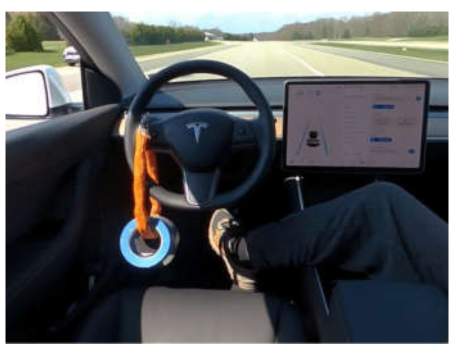
- Hack Google Maps?

Machine Learning: Security

- Can we mislead **Tesla**?

Machine Learning: Security

- Can we mislead **Tesla**?



Machine Learning: Security

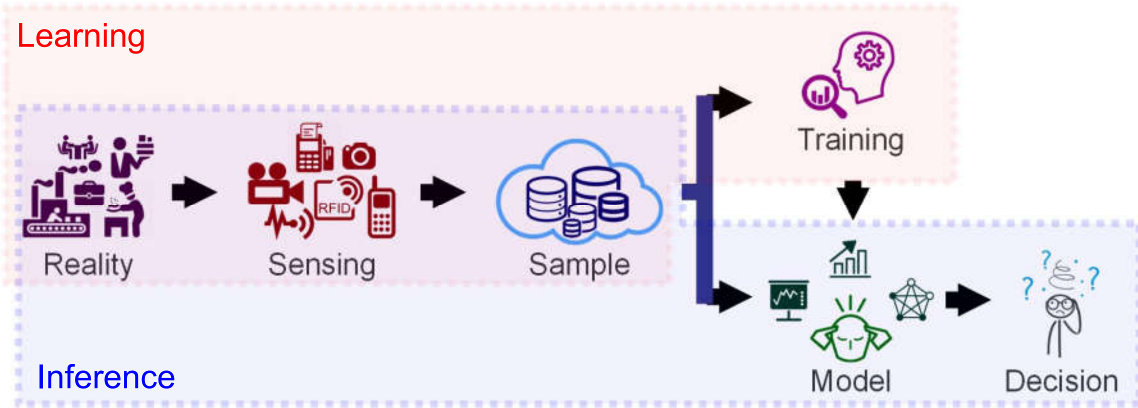
- Can we mislead **Tesla**?

https://keenlab.tencent.com/zh/2019/03/29/Tencent-Keen-Security-Lab-Experimental-Security-Research-of-Tesla-Autopilot/

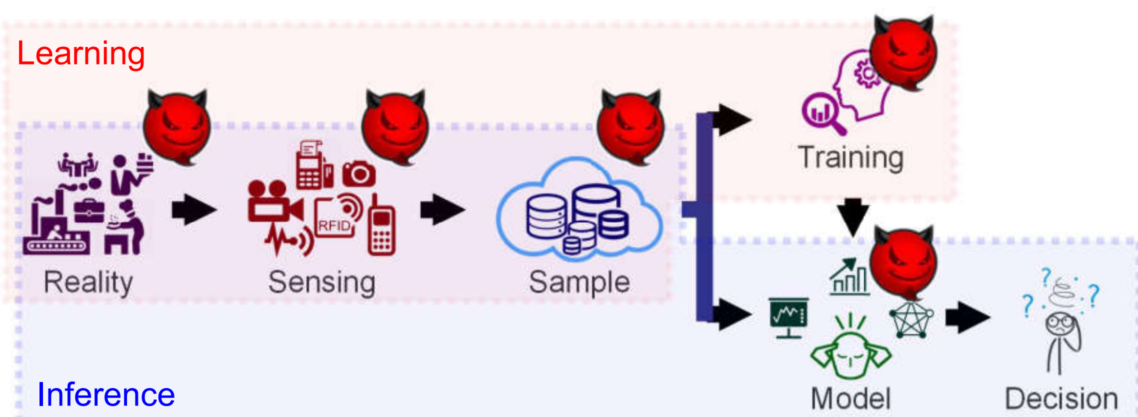
Machine Learning: Security

- Security issues of Machine Learning techniques have not been investigated deeply before applying them to the real world
- A machine learning system can be fooled much easier than one might imagine

- **Machine Learning**
  Algorithm is improved automatically by using data
- Two phases: Learning + Inference

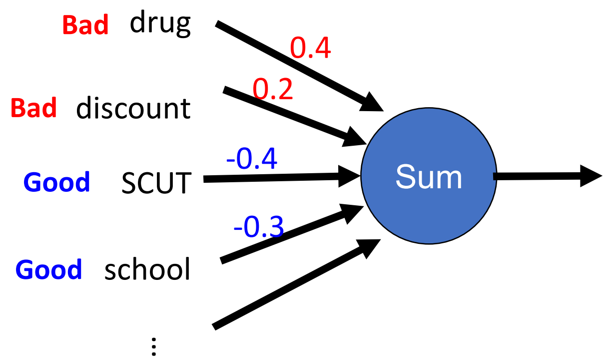


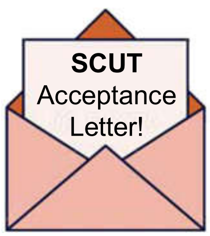
- An **adversary** may exist at anywhere to mislead a model
  - Especially in a security-related application



Example

- **Junk Mail Filter**
  Classify if an email is a junk mail
  - Positive: Junk Mail (Spam)
  - Negative: Legitimate Mail (Ham)
- A linear Classifier with Boolean features indicating whether a word is present
  - **Bad Word**
    positive weight
  - **Good Word**
    negative weight

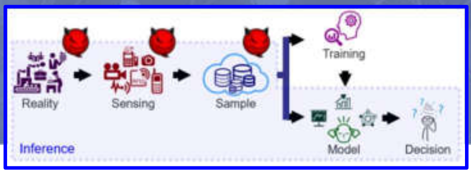




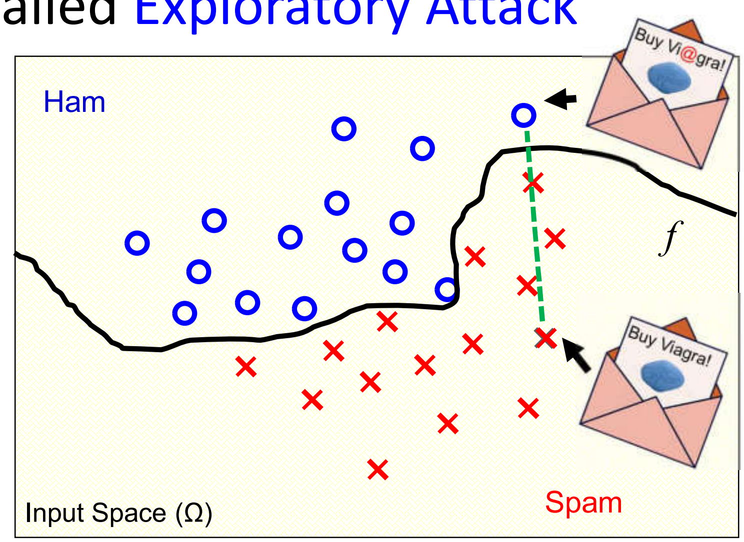
SCUT	-0.4	Good Word
Acceptance	0.1	Bad Word
Letter	N/A	Natural Word

Total = -0.3. It is Legitimate!

Evasion Attack



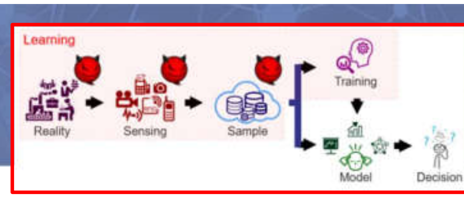
- Mislead trained models
- Also called Exploratory Attack



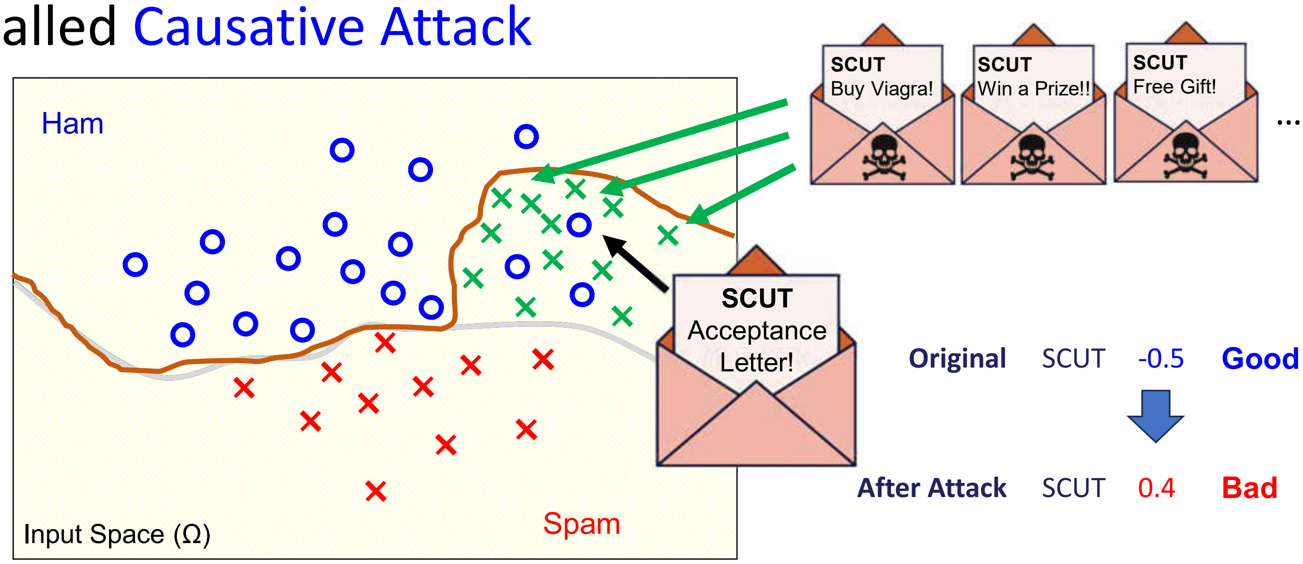
A bad word (Viagra, 0.8) is removed but its meaning is still here!

Viagra	0.8	Bad
Buy	0.1	Bad

Poisoning Attack

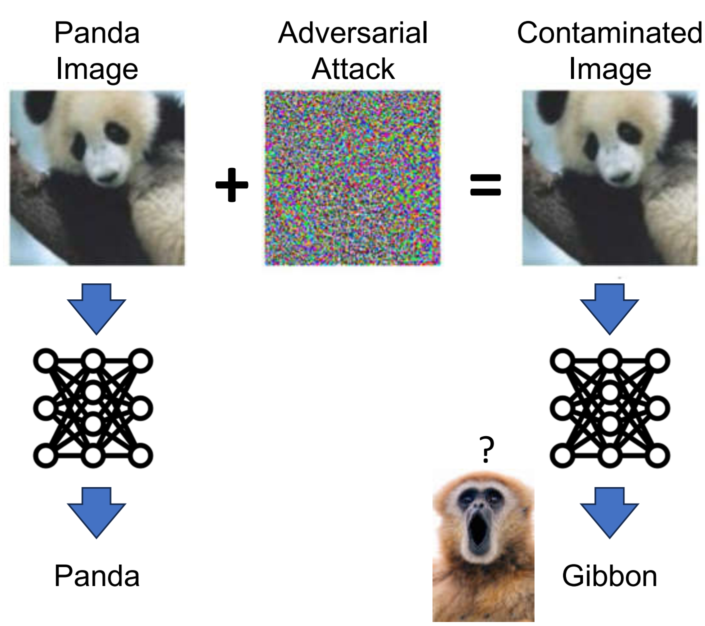


- Affect a training process
- Also called Causative Attack



Example: Classification

- Adversarial Attack is commonly discussed in classification problems
  - Personal Identification (Face, fingerprint…)
  - Object Identification (Sign…)



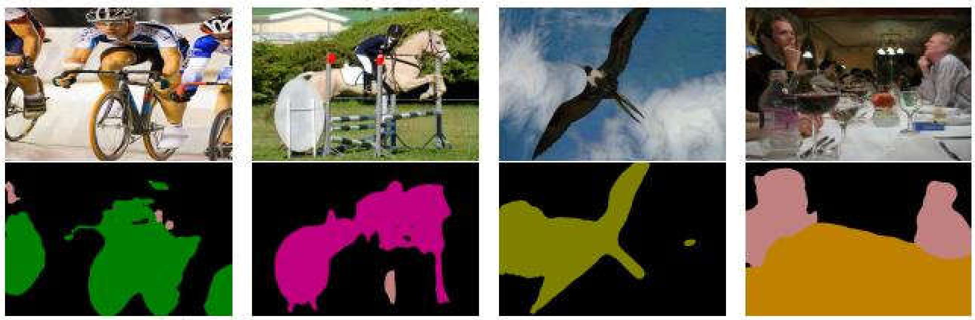
Example: Segmentation

Original Images

Objects can be identified

Contaminated Images

Objects cannot be identified



Gu, J., Zhao, H., Tresp, V., & Torr, P. H. (2022). Segpgd: An effective and efficient adversarial attack for evaluating and boosting segmentation robustness. In European Conference on Computer Vision.

Example: Recommender System

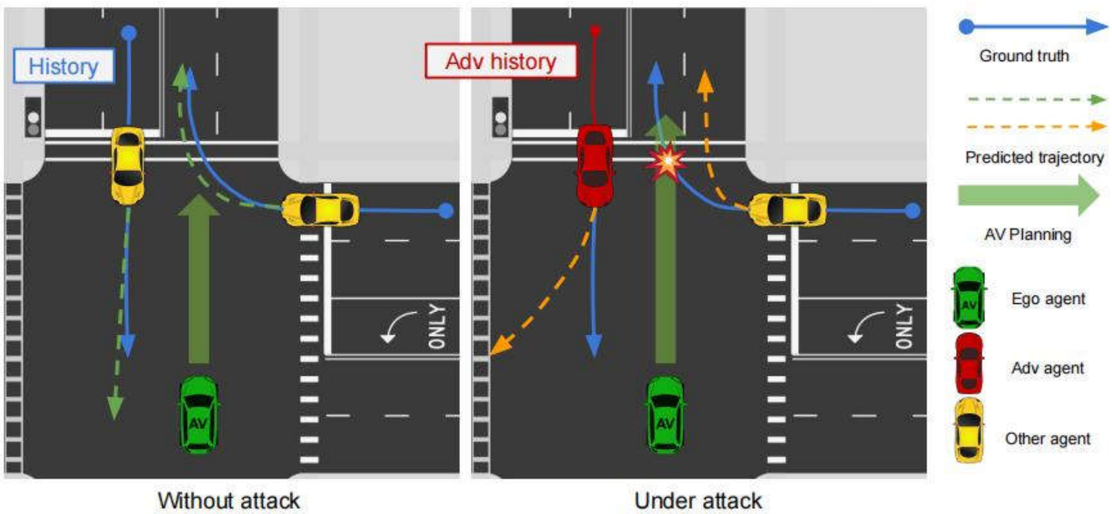
- Retailers want products rank at the top to increase the sales
  - Aim to manipulate rankings by injection fake user profiles
    - Push Attack: recommend more
    - Nuke Attack: recommend less

	Item1	Item2	Item3	Item4	Item5	Item k	
Alice	5	3	/	4	/	?	
User1	3	/	2	3	5	2	sim(Alice, User1) =1
User2	/	3	4	3	3	1	sim(Alice, User2) =0.87
User3	3	/	/	2	/	4	sim(Alice, User3) =0
Fake1	5	3	/	/	/	5	sim(Alice, Fake1) =0.96
Fake2	5	/	2	4	/	5	sim(Alice, Fake2) =0.92
Fake3	/	3	/	4	/	5	sim(Alice, Fake2) =0.99

M Si, Q Li (2020)Shilling attacks against collaborative recommender systems: a review. In: Artificial Intelligence Review, 53(1), 291-319

Example: Autonomous Driving

- Mislead the predicted trajectories by slightly adjusting the history trajectory of one car



Cao, Y., Xiao, C., Anandkumar, A., Xu, D., & Pavone, M. (2022). Advdo: Realistic adversarial attacks for trajectory prediction. In European Conference on Computer Vision.

Comparison

- Methods dealing with outliers and noise may not work in adversarial environment
  - Outlier
    - Model Independent
    - Very different from normal
  - Adversarial Attack
    - Design based on model
    - May camouflage as normal samples

  - Stochastic Noise
    - Model Independent
    - Follow a distribution
    - Slightly different from normal
  - Adversarial Attack
    - Design based on model
    - Can be in any shape
    - A few attack samples may significantly downgrade performance

Why Vulnerable?

1. Aim of Machine Learning

- A ML system typically aims to maximize performance, i.e. accuracy & efficiency
- Security is usually neglected

Why Vulnerable?

2. Machine Learning Assumptions

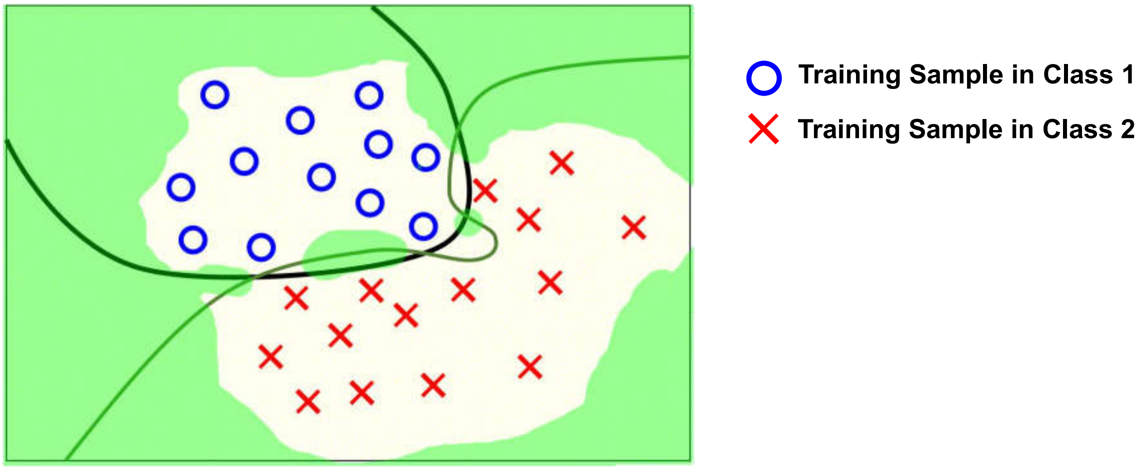
- Samples are independent and identically distributed (i.i.d.)
- Training and test samples follow the same (similar) distributions
- Implication:
  - 100% trust in the samples
  - Not consider a change of distribution
  - Samples are independent of a model

- All are violated by adversarial attacks

Why Vulnerable?

3. Uncertain situations

- Samples are limited but the space is infinite



Is Your ML System Safe?

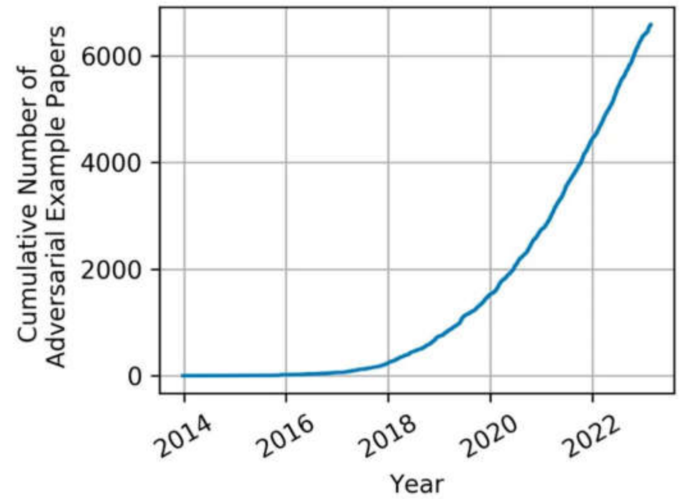
- How can we know whether it is safe?
  - Try to attack it! Identify vulnerabilities
- Then, Improve its robustness

- Arms race between adversary and defender

B. Biggio, G. Fumera, F. Roli(2014) Security evaluation of pattern classifiers under attack. In: IEEE transactions on knowledge and data engineering

Adversarial Learning

- **Adversarial Learning**
  Study on machine learning in adversarial environments in which decisions of models will be misled



Nicholas Carlini, "A Complete List of All (arXiv) Adversarial Example Papers"

Adversary's Aspect

Adversary's Goal

Adversary's Capability

Adversary's Knowledge

Barreno et al., Can Machine Learning Be Secure? ASIACCS '06

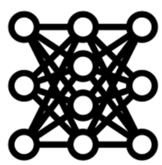
Adversary’s Goal

- **Cause security violation**
  - An adversary forces a ML system to
    - **Learn wrong** things
    - **Do wrong** things
    - **Reveal wrong** things

Integrity	Availability	Confidentiality/Privacy
Mis-operate on some situations but do not compromise normal ones	Compromise normal system operation	Reveal confidential information

Barreno et al., Can Machine Learning Be Secure? ASIACCS ’06

Adversary’s Knowledge



Machine Learning System

Trained Parameters	Learning Parameters	Model	Model’s Output	Training Sample	Feature Space

Perfect Knowledge	Limited Knowledge	No Knowledge
White-box	**Grey-box**	**Black-box**
ALL knowledge	**Partial** knowledge	**“No”** knowledge (Feature Space may be obtained)

B. Biggio, G. Fumera, F. Roli, IEEE TKDE 2014

Adversary's Capability

- Adversary should **not be omnipotent**
  - Messages of an email should be delivered to human
  - Malware must able to be executed and generate some damages
- **Concealment** should be considered
  - Contaminated samples should be similar to the clean ones
- **Constrains**
  - Number of manipulated samples
  - Number of manipulated features
  - Maximum amount of modifications on a feature

Adversary's Capability

Attack Type	Training Phase	Inference Phase	Manipulation
Evasion Attack	No	Yes	Feature
Poisoning Attack	Yes	No (maybe)	Feature / Label / Model

Attack Types

Attacker's Capability		Attacker's Goal		
		Integrity Mis-operate on some situations but do not compromise normal ones	**Availability** Compromise normal system operation	**Privacy / Confidentiality** Reveal confidential information
Attacker's Capability	**Test data**	Evasion (Adversarial Attack)	Sponge Attacks	Model Stealing Training Set Recovery
	Training data	Integrity Poisoning e.g. Targeted Poisoning Attack, Backdoor Attack	Indiscriminate Poisoning Attack, e.g. DoS	/

Biggio & Roli, Wild Patterns, PR 2018 https://arxiv.org/abs/1712.03141

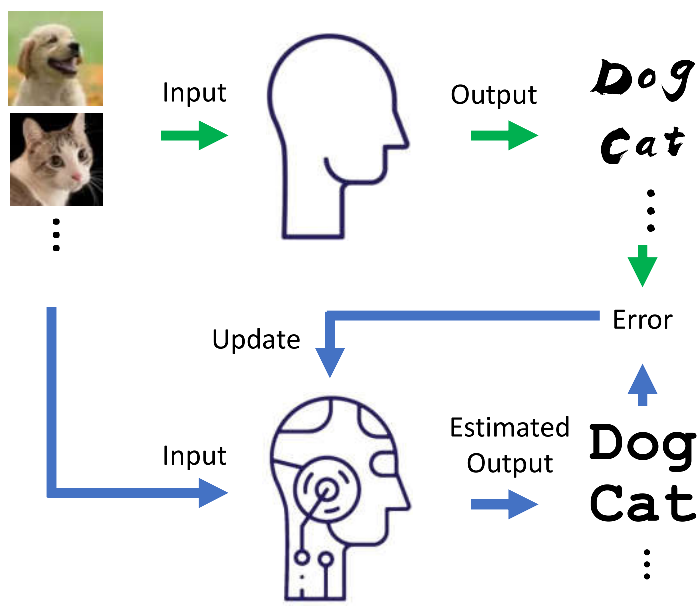
Course Syllabus

- Ch01 Overview
- Ch02 Evasion Attacks
  & Countermeasures
- Ch03 Poisoning Attacks
  & Countermeasures
- Ch04 Privacy Attacks & Countermeasures
  Physical Attacks
  Non-Security Applications
  Conclusion

Refresher on Machine Learning

Machine Learning

- Machine Learning can be treated as Function Approximation



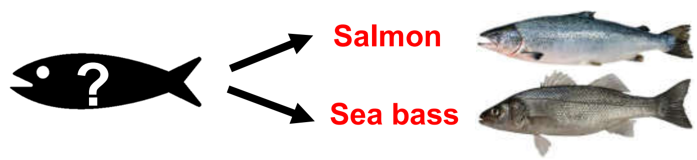
What is Learning?

- A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.

Task T
Separate Salmon and Sea Bass

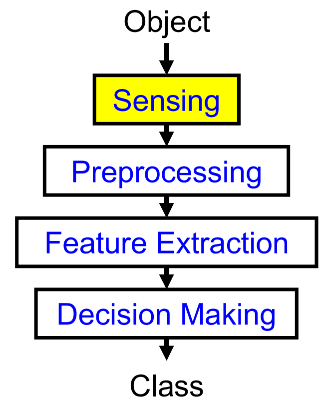
Performance P
Accuracy on identification

Experience E
Caught Salmon and Sea Bass



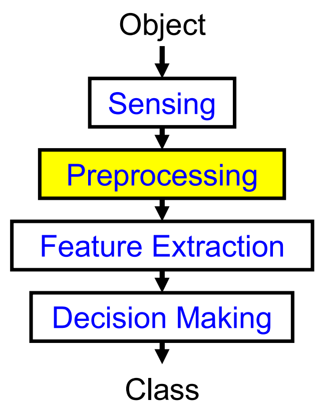
Machine Learning Procedure
Sensing

- **Digitize** the object to the format which can be handled by machines
- Example
  - Type of Device
    Camera? Depth Camera? Infra-red? Ultrasound? Movement Sense? Combination?
  - Setting of Device
    Number? Angle? Overlap shooting range?
  - Background
    Lighting? Background simplicity?



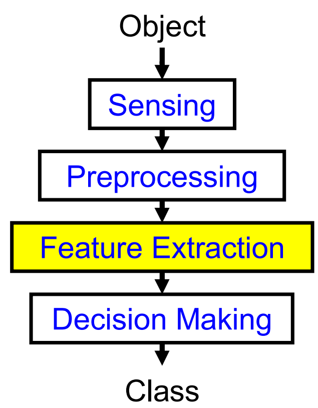
Preprocessing

- **Refine** the data
- Example
  - Lighting conditions
  - Position of fish
  - Angle of fish
  - Noise
  - Blurriness
  - Segmentation (remove object from background)



Feature Extraction

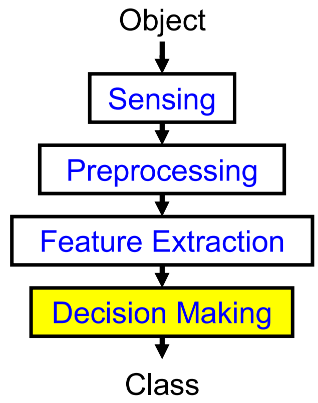
- Decide which **information** is able to distinguish classes
- Example
  - Length, width, weight, number and shape of fins, tail shape, etc.
- Rely on technical background and common sense
  - Experts may help



Machine Learning Procedure

Decision Making

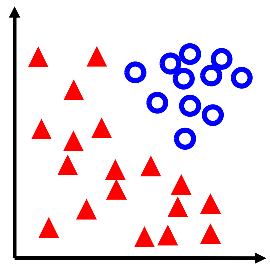
- Decision Type:
  - Class (Classification)
  - Value (Regression, Value Prediction)
  - Rank (Ranking)
  - Action (Reinforcement Learning)
  - Region (Segmentation)
- Many machine learning techniques are available



Classification

- **Classification** is mainly focused in this course
  - An important ad popular application of machine learning
  - Aim to assign a sample to a class
  - Sample = Feature Vector : $\boldsymbol{x} = [x_1, x_2, \dots, x_d] \in X$
    - d : feature number
  - Class : $y \in Y, Y = \{y_1, y_2, \dots, y_c\}$
    - c : class number

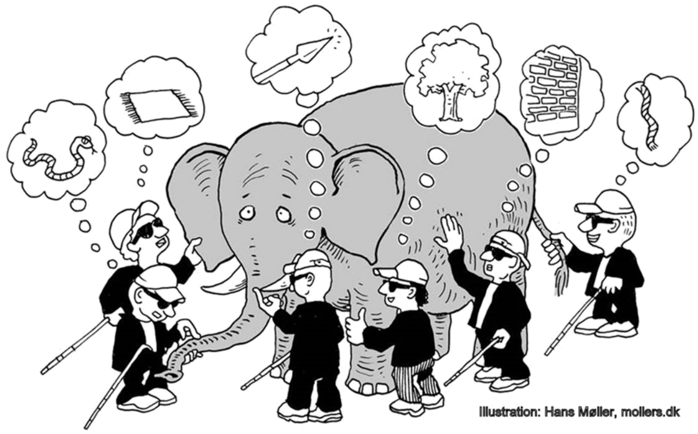
One Dimension



Two Dimensions

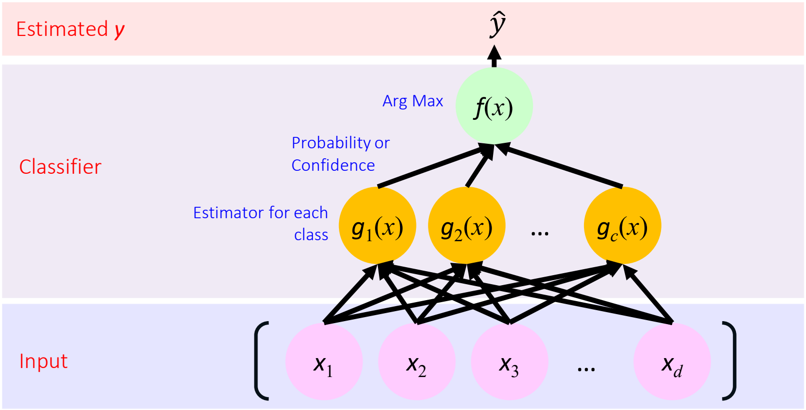
Classification: Formulation

- How to formulate a classification problem $X \rightarrow Y$?
  - Input sample X is a real vector
  - Class Y is discrete
  - Not convenient to calculate, e.g. 1 + 2 + 3 = Class 1?



Classification: Formulation

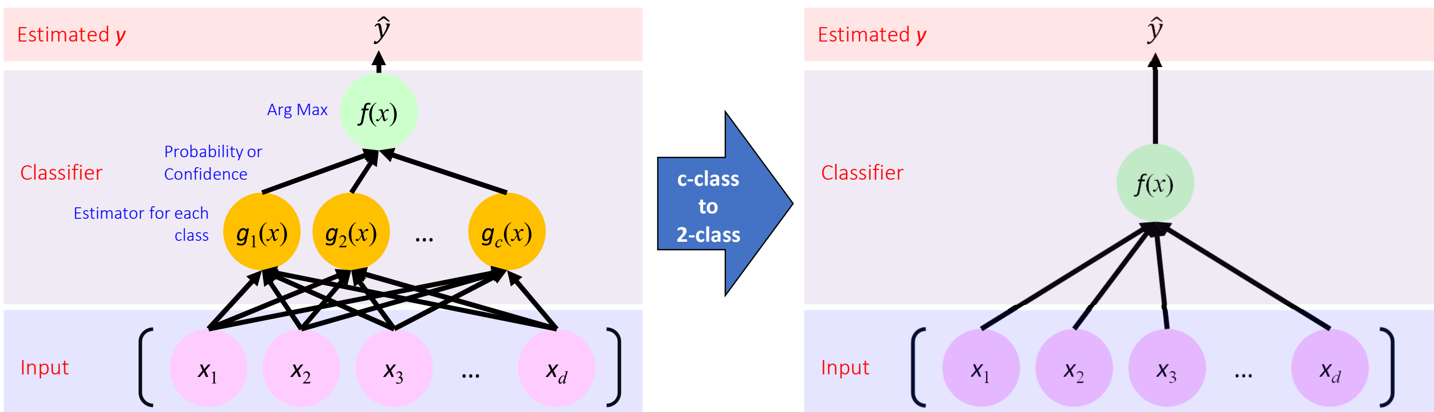
- Probability Estimation of x belongs to a class
  - Contains a set of discriminant functions $g_i(\boldsymbol{x})$, $i = 1, \ldots, c$ indicates how likely $\boldsymbol{x}$ belongs to y_i
  - $\boldsymbol{x}$ is assigned to class y_i if $g_i(x)$ is max for $i = 1 \ldots c$



Classification: Formulation

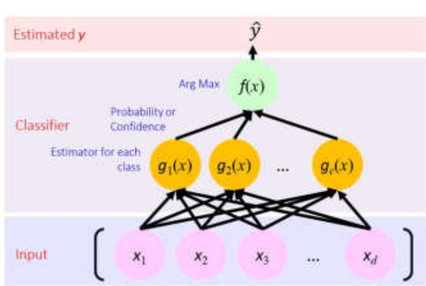
- A two-class problem is a special case
  - Only one function is required

$$g_1(x) > g_2(x),\ x \text{ belongs to class 1}$$
$$g_1(x) - g_2(x) > 0$$
$$f(x) > 0$$



Classification: Formulation

Multi-Class Problem



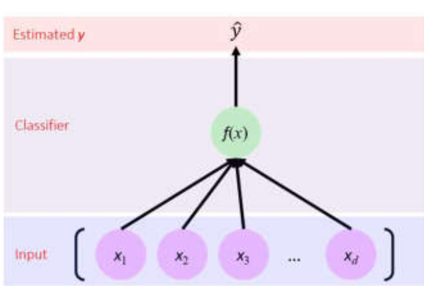
Original Dataset

x	y
23	1
42	2
52	3
12	4

$g_1(\boldsymbol{x})$: x	$y^{(1)}$	$g_2(\boldsymbol{x})$: x	$y^{(2)}$	$g_3(\boldsymbol{x})$: x	$y^{(3)}$	$g_4(\boldsymbol{x})$: x	$y^{(4)}$
23	1	23	0	23	0	23	0
42	0	42	1	42	0	42	1
52	0	52	0	52	1	52	0
12	0	12	0	12	0	12	0

$$Loss = \sum_{i=1}^{c} \left(g_i(\boldsymbol{x}) - y^{(i)}\right)^2$$

Two-Class Problem



Original Dataset

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52	2
12	2

$f(\boldsymbol{x})$

x	y
23	1
42	1
52	-1
12	-1

$$Loss = (f(\boldsymbol{x}) - y)^2$$

Classification: Formulation

- Can a multi-class problem also be formulated like this?

Original Dataset

x	y
23	1
42	2
52	3
12	4

$g(\boldsymbol{x})$

x	y
23	1
42	2
52	3
12	4

$$Loss = (g(\boldsymbol{x}) - y)^2$$

$$f(x) = \begin{cases} y_1 & g(x) < 1.5 \\ y_2 & 1.5 \le g(x) < 2.5 \\ y_3 & 2.5 \le g(x) < 3.5 \\ y_4 & 3.5 \le g(x) \end{cases}$$

Original Dataset

x	y
23	1
42	2
52	3
12	4

$g_1(\boldsymbol{x})$: x	$y^{(1)}$	$g_2(\boldsymbol{x})$: x	$y^{(2)}$	$g_3(\boldsymbol{x})$: x	$y^{(3)}$	$g_4(\boldsymbol{x})$: x	$y^{(4)}$
23	1	23	0	23	0	23	0
42	0	42	1	42	0	42	1
52	0	52	0	52	1	52	0
12	0	12	0	12	0	12	0

$$Loss = \sum_{i=1}^{c} \left(g_i(\boldsymbol{x}) - y^{(i)}\right)^2$$

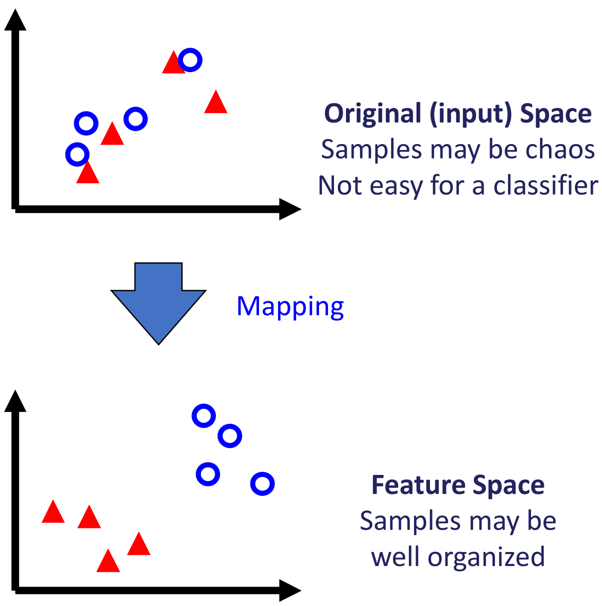
$f(x) = y_i$, where $i = \underset{j}{argmax}\, g_j(x)$

Classification: Loss Function

- Aim to minimize **the loss function**
  - Less loss means better performance
- Different levels of description
  - Loss function on a sample $\quad L = (f(x) - y)^2$
  - Loss function including explicit w on a sample $\quad L(\boldsymbol{w}) = (f_{\boldsymbol{w}}(x) - y)^2 \quad$ w denotes the parameters
  - Loss function including explicit w on n samples (usually mean training set) $\quad L(\boldsymbol{w}) = \sum_{i=1}^{n} (f_{\boldsymbol{w}}(\boldsymbol{x}_i) - y_i)^2$

Mapping

- Practically, a classification problem is complicated
- Not easily to train a complicated classifier with good performance
- Map samples to a high-dimensional space, which may separate classes better than the original space

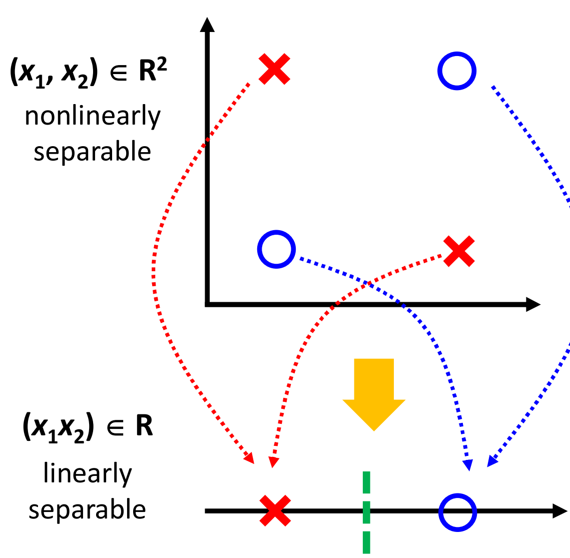


Mapping

- XOR Example

x_1	x_2	y
1	1	1
-1	1	-1
1	-1	-1
-1	-1	1

x_1	x_2	x_1x_2	y
1	1	1	1
-1	1	-1	-1
1	-1	-1	-1
-1	-1	1	1



Mapping

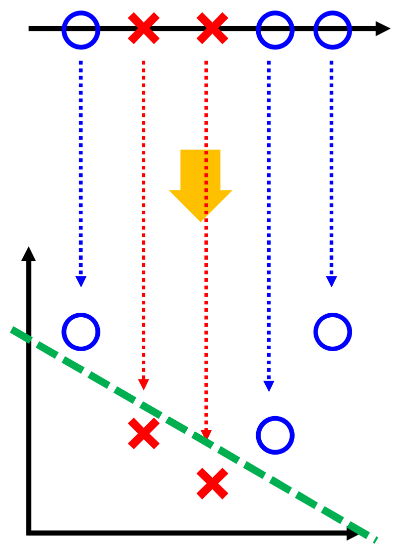
- Another Example

x	y
-2	1
-1	-1
0	-1
1	1
2	1

x	x	x^2	y
-2	-2	4	1
-1	-1	1	-1
0	0	0	-1
1	1	1	1
2	2	4	1

(x) ∈ R
nonlinearly separable

(x, x^2) ∈ R^2
linearly separable



Classifier
SVM: Linearly Separable

- Support Vector Machine (SVM)
- Problem can be formulated as Quadratic Optimization Problem and solve for w and b

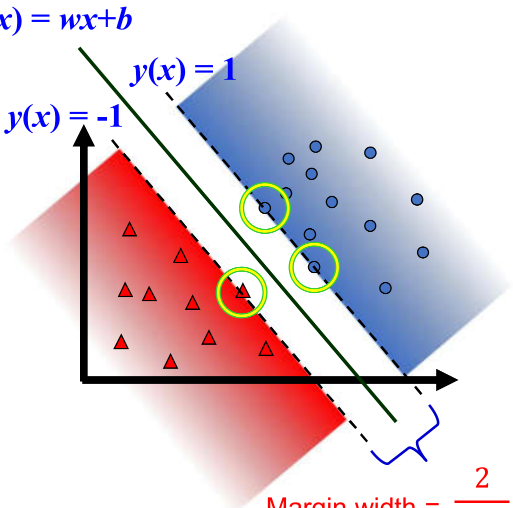
Margin Width

$$\underset{w,\,b}{\text{minimize}} \quad \frac{1}{2}\|w\|^2$$

$$\text{subject to} \quad y_i(w^T x_i + b) \geq 1$$

$$\text{where} \quad i = 1 \ldots n \quad \text{and} \quad y = \{1, -1\}$$

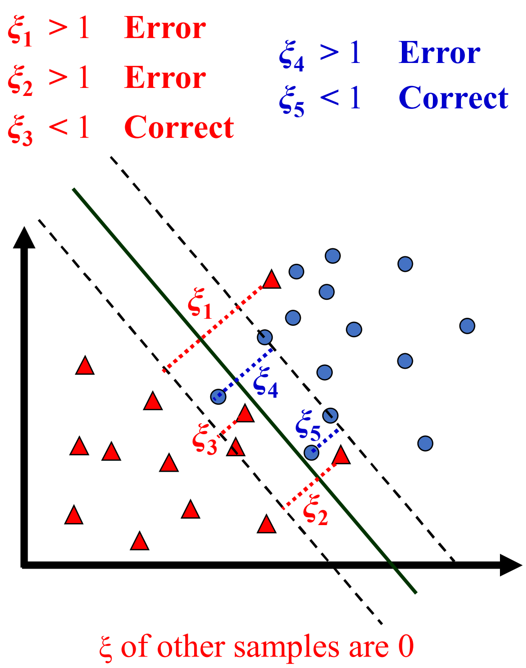
All samples should be behind the margin



Margin width = $\frac{2}{\|w\|}$

Classifier

SVM: Non-Linearly Separable



- **Slack Variable (ξ)** is added as a punishment to allow a sample in / far away from the margin
- Optimization:

Margin Width　　Punishment

$$\underset{w,\ b}{\text{Minimize}}\ \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\xi_i$$

$$\text{subject to } y_i(w^T x_i + b) \geq 1 - \xi_i \quad i = 1\ldots N$$

$$\xi_i \geq 0$$

Punishment allow a sample not behind the margin

where

C : tradeoff parameter between error and margin

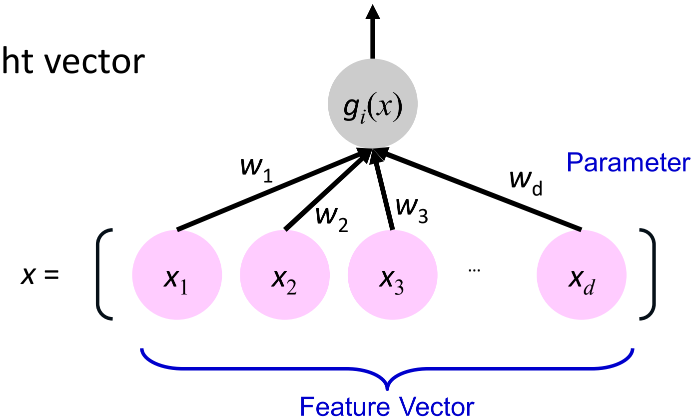
Classifier

Linear Discriminant Function

- LDF: a linear combination of x

$$g(x) = \sum_{i=1}^{d} w_i x_i$$

w : is the weight vector



- **How to train g(x)?**
  - Minimize

$$L(w) = \frac{1}{2n}\sum_{i=1}^{n}\left(g_w\left(x^{(i)}\right) - y^{(i)}\right)^2$$

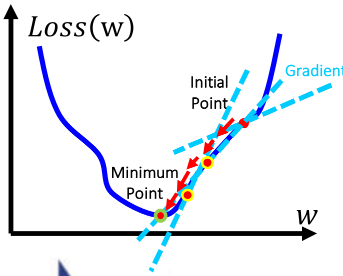
Gradient Descent

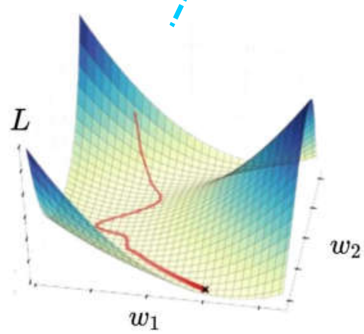
- When h_{w} is differentiable, gradient descent can be used to minimize the Loss Function

- Influence on $L(\mathrm{w})$ by changing w slightly

$$\boldsymbol{w}^{(t+1)} = \boldsymbol{w}^{(t)} - \alpha \frac{\partial L(\boldsymbol{w}^{(t)})}{\partial \boldsymbol{w}}$$

  - α : the learning rate
  - $\boldsymbol{w}^{(t)}$: the parameters at the time t



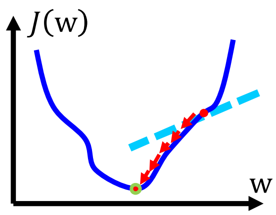


Gradient Descent

- **Algorithm**
  - Start with an arbitrarily chosen weight $\mathrm{w}^{(1)}$
  - Let t = 0
  - Loop
    - t = t + 1
    - Compute gradient vector $\partial Loss(\mathrm{w}^{(t)})/\partial \mathrm{w}$
    - Next value $\mathrm{w}^{(t+1)}$ determined by moving some distance from $\mathrm{w}^{(t)}$ in the direction of the steepest descent

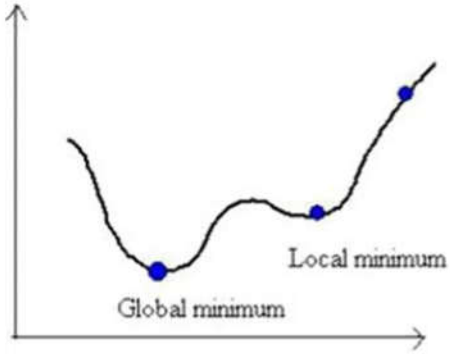
$$\mathrm{w}^{(t+1)} = \mathrm{w}^{(t)} - \alpha \frac{\partial Loss(\mathrm{w}^{(t)})}{\partial \mathrm{w}}$$

      - i.e., along the negative of the gradient
  - Until Finish Training (Control by number of updates or size of $\partial Loss(\mathrm{w}^{(t)})/\partial \mathrm{w}$)



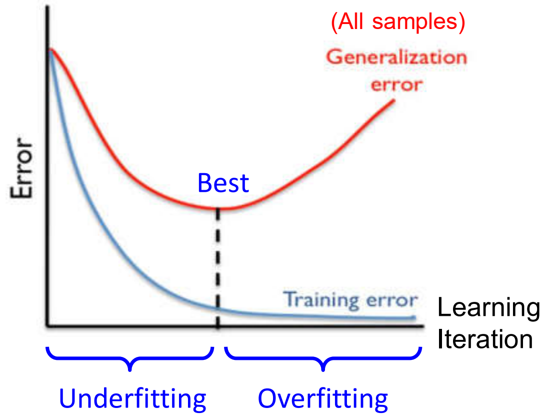
Gradient Descent

- Related Issues:
  - Size of Learning Rate (α)
    - Too small, convergence is needlessly slow
    - Too large, the correction process will overshoot and cannot even diverge
  - Sub-optimal Solution
    - Trapped by local minimum



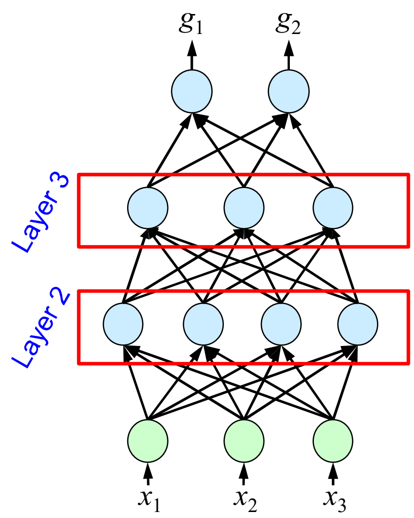
Gradient Descent

- What is the objective of a classifier?
  - Classify training samples accurately?
    - Training Error (Empirical Error) (R_{emp})
      - Error of the training samples, computable
      - Training Objective
  - Classify unseen samples accurately?
    - Generalization Error (R_{gen})
      - Non-computable, estimate only
      - Ultimate Objective
- Training and ultimate objectives are correlated but different

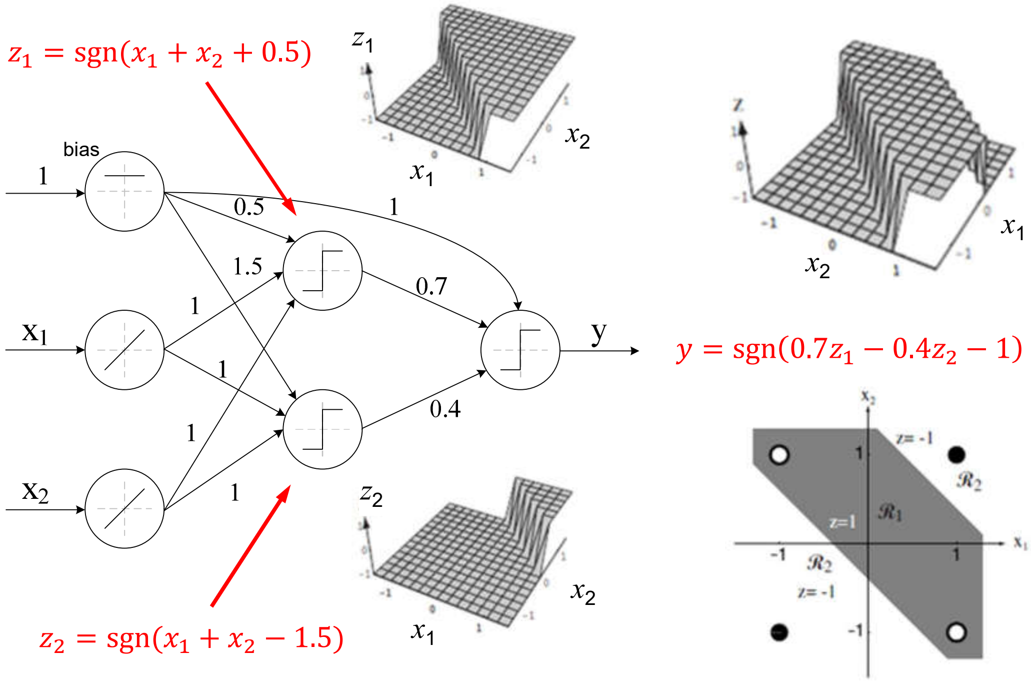


Multi-Layer Perceptron

- Multi-Layer Perceptron
  - Neurons are arranged in layers
  - A neuron is connected to all neurons in next layer
    - Fully-connected
    - Feedforward
  - Neurons may have different activation functions or no activation function



XOR Example

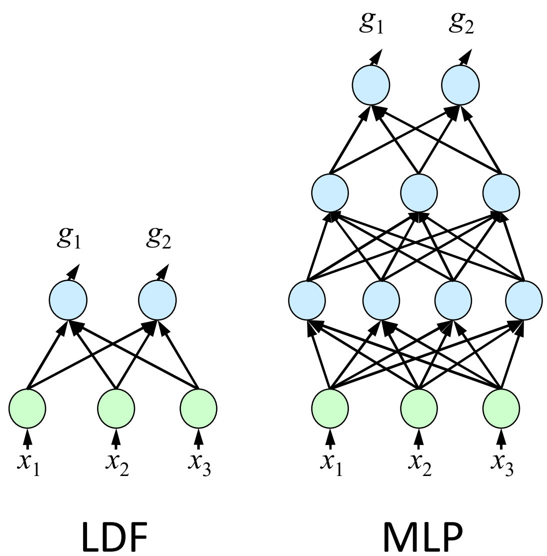


Backpropagation

- How to determine the weight?
  - Gradient Descent

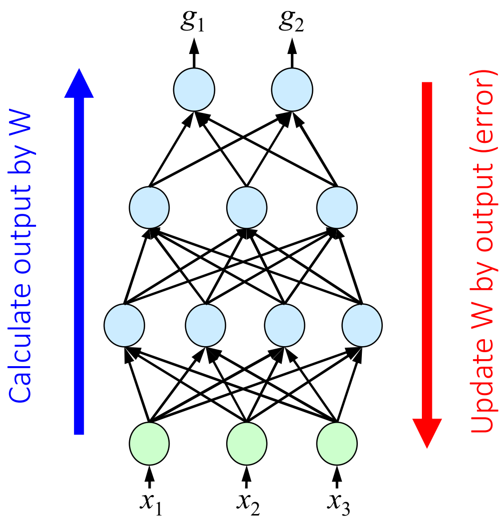
$$w^{(k+1)} = w^{(k)} + \alpha \frac{\partial J(w^{(k)})}{\partial w}$$

    - α: the learning rate
    - How to calculate $\partial J(w)/\partial w$ for each w?



Backpropagation

- Backpropagation
  - Calculation of the derivative flows backwards through the network



Classifier: Multi-Layer Perceptron

Backpropagation

- Recall, Chain rule

$$f(x) = sin(\cos(x^2))$$

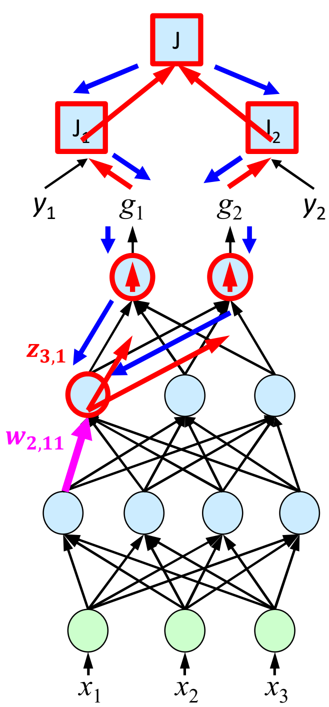
$$\frac{\partial f(x)}{\partial x} = \frac{\partial sin(\cos(x^2))}{\partial x}$$

$$= \frac{\partial sin(\cos(x^2))}{\partial \cos(x^2)} \frac{\partial \cos(x^2)}{\partial x}$$

$$= \frac{\partial sin(\cos(x^2))}{\partial \cos(x^2)} \frac{\partial \cos(x^2)}{\partial x^2} \frac{\partial x^2}{\partial x}$$

Classifier: Multi-Layer Perceptron: Backpropagation

Example



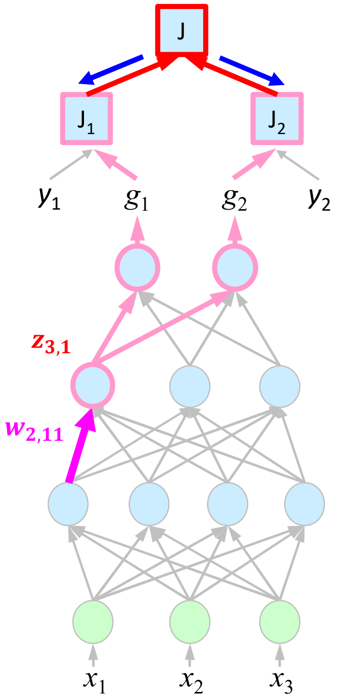
- Which paths to the output are affected by $w_{2,11}$?
- Error on each output should be considered

$$J\left(w^{(k)}\right) = J_1 + J_2$$

- Backprop from J to $w_{2,11}$

Classifier: Multi-Layer Perceptron: Backpropagation

Example



$$\frac{\partial J(w^{(k)})}{\partial w_{2,11}}$$

$$\frac{\partial J(w^{(k)})}{\partial w_{2,11}}$$

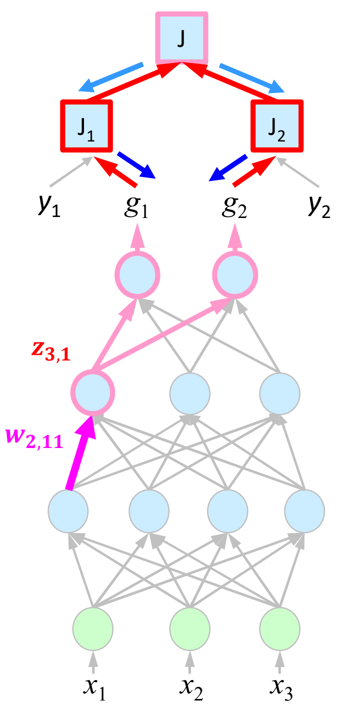
$$= \frac{\partial (J_1 + J_2)}{\partial w_{2,11}}$$

$$= \sum_{i=1}^{2} \frac{\partial J_i}{\partial w_{2,11}}$$

$$\boxed{J(w^{(k)}) = J_1 + J_2}$$

Classifier: Multi-Layer Perceptron: Backpropagation

Example



$$\frac{\partial J(w^{(k)})}{\partial w_{2,11}} = \sum_{i=1}^{2} \frac{\partial J_i}{\partial w_{2,11}}$$

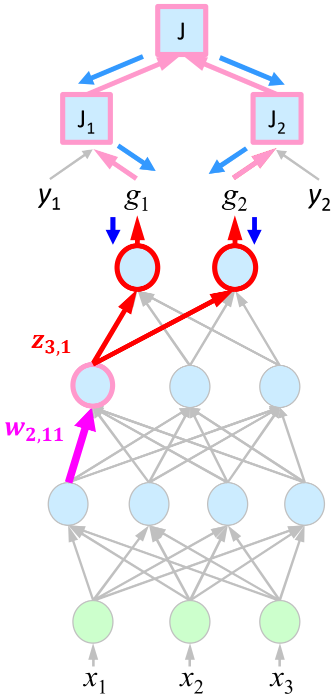
$$\frac{\partial J_i}{\partial w_{2,11}}$$

$$= \frac{\partial \frac{1}{2}(y_i - g_i)^2}{\partial w_{2,11}}$$

$$= -(y_i - g_i)\frac{\partial g_i}{\partial w_{2,11}}$$

$$\boxed{J_i = \frac{1}{2}(y_i - g_i)^2}$$

Example



$$\frac{\partial J(w^{(k)})}{\partial w_{2,11}} = -\sum_{i=1}^{2} (y_i - g_i)\frac{\partial g_i}{\partial w_{2,11}}$$

$$\frac{\partial g_i}{\partial w_{2,11}}$$

$$= \frac{\partial a\left(\sum_{j=1}^{3} z_{3,j}\, w_{3,ji}\right)}{\partial w_{2,11}}$$

$$\boxed{g_i = a\left(\sum_{j=1}^{3} z_{3,j}\, w_{3,ji}\right)}$$

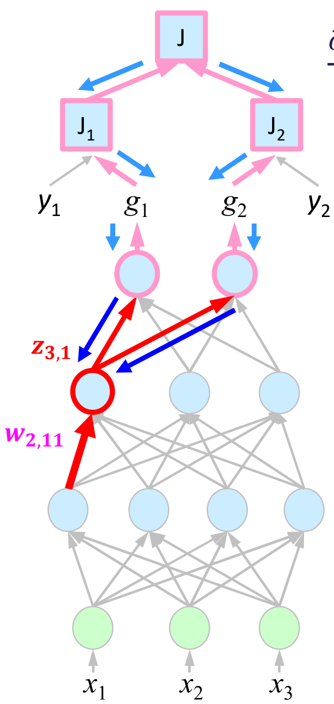
$$= \frac{\partial a\left(\sum_{j=1}^{3} z_{3,j}\, w_{3,ji}\right)}{\partial\left(\sum_{j=1}^{3} z_{3,j}\, w_{3,ji}\right)} \frac{\partial\left(\sum_{j=1}^{3} z_{3,j}\, w_{3,ji}\right)}{\partial w_{2,11}}$$

$$\boxed{\text{Let } a'(x) = \frac{\partial a(x)}{\partial (x)}}$$

$$= a'\left(\sum_{j=1}^{3} z_{3,j}\, w_{3,ji}\right)\frac{\partial\left(z_{3,1}w_{3,1i} + z_{3,2}w_{3,2i} + z_{3,3}w_{3,3i}\right)}{\partial w_{2,11}}$$

$$= a'\left(\sum_{j=1}^{3} z_{3,j}\, w_{3,ji}\right) w_{3,1i}\frac{\partial z_{3,1}}{\partial w_{2,11}}$$

Example



$$\frac{\partial J(w^{(k)})}{\partial w_{2,11}} = -\sum_{i=1}^{2}\left((y_i - g_i)a'\left(\sum_{j=1}^{3} z_{3,j}\, w_{3,ji}\right) w_{3,1i}\frac{\partial z_{3,1}}{\partial w_{2,11}}\right)$$

$$\frac{\partial z_{3,1}}{\partial w_{2,11}}$$

$$= \frac{\partial a\left(\sum_{k=1}^{4} z_{2,k}\, w_{2,k1}\right)}{\partial w_{2,11}}$$

$$\boxed{z_{3,1} = a\left(\sum_{k=1}^{4} z_{2,k}\, w_{2,k1}\right)}$$

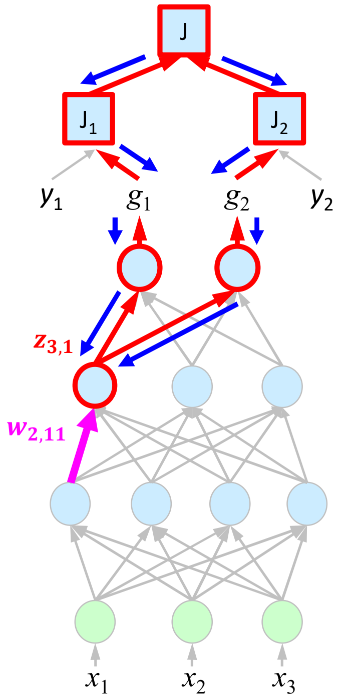
$$= \frac{\partial a\left(\sum_{k=1}^{4} z_{2,k}\, w_{2,k1}\right)}{\partial\left(\sum_{k=1}^{4} z_{2,k}\, w_{2,k1}\right)} \frac{\partial\left(\sum_{k=1}^{4} z_{2,k}\, w_{2,k1}\right)}{\partial w_{2,11}}$$

$$\boxed{a'(x) = \frac{\partial a(x)}{\partial (x)}}$$

$$= a'\left(\sum_{k=1}^{4} z_{2,k}\, w_{2,k1}\right)\frac{\partial\begin{pmatrix} z_{2,1}w_{2,11} + z_{2,2}w_{2,21} + \\ z_{2,3}w_{2,31} + z_{2,4}w_{2,41}\end{pmatrix}}{\partial w_{2,11}}$$

$$= a'\left(\sum_{k=1}^{4} z_{2,k}\, w_{2,k1}\right) z_{2,1}$$

Example

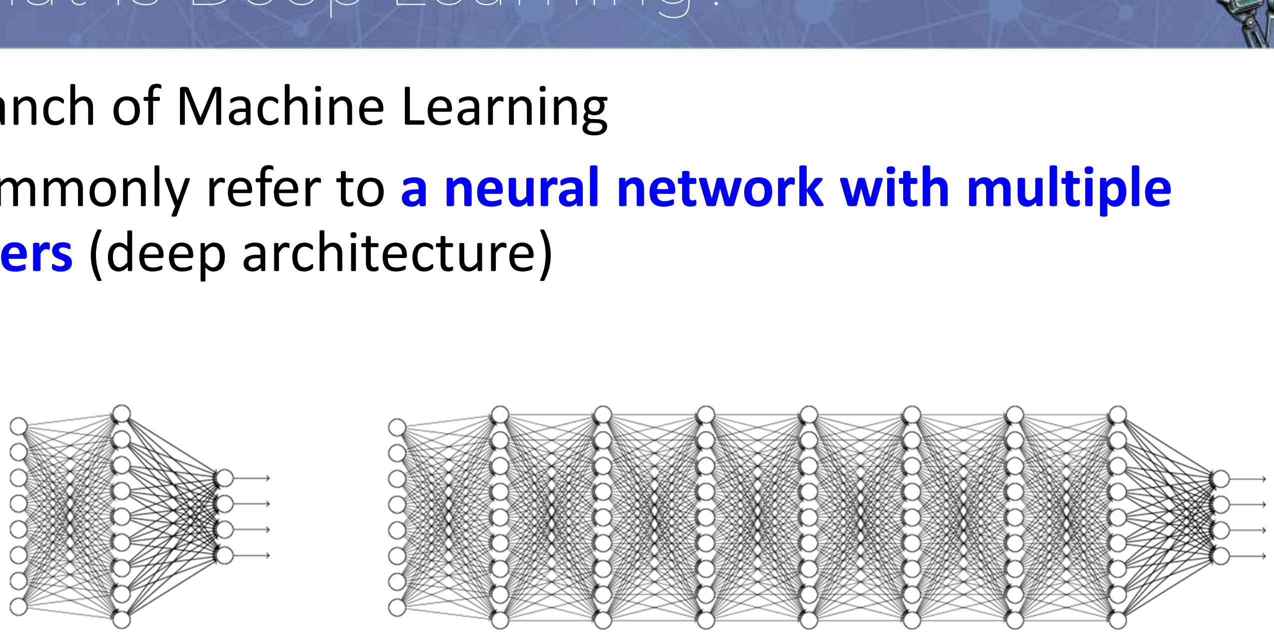


$$\frac{\partial J(w^{(k)})}{\partial w_{2,11}} = -\sum_{i=1}^{2} \begin{pmatrix} (y_i - g_i)a'\left(\sum_{j=1}^{3} z_{3,j}\, w_{3,ji}\right) w_{3,1i} \\ a'\left(\sum_{k=1}^{4} z_{2,k}\, w_{2,k1}\right) z_{2,1} \end{pmatrix}$$

$$\boxed{a'(x) = \frac{\partial a(x)}{\partial (x)}}$$

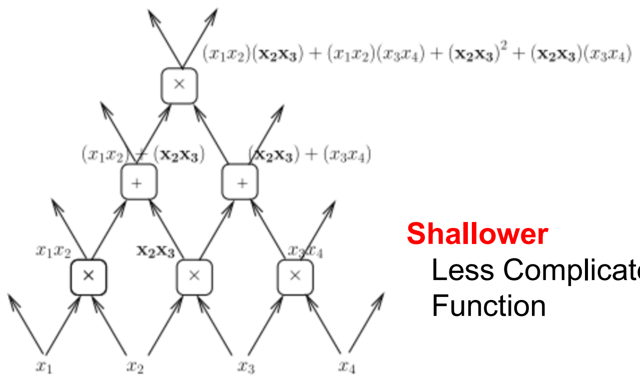
What is Deep Learning?

- Branch of Machine Learning
- Commonly refer to **a neural network with multiple layers** (deep architecture)



Why Deep Learning?

- Our brain is a very deep architecture
- A deep architecture can represent more complicated function than a shallow one



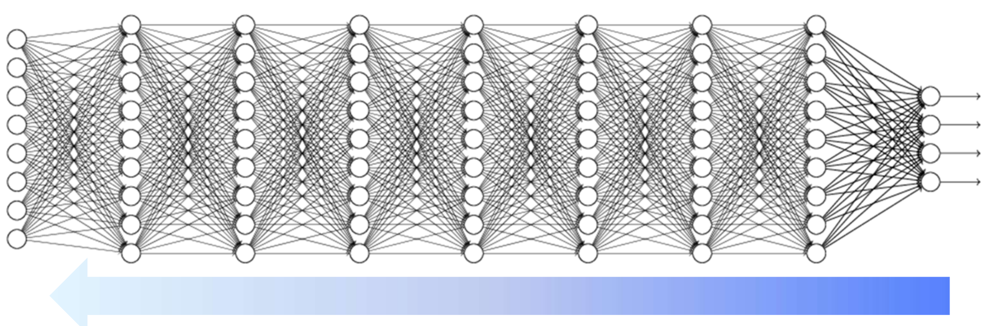
Deeper
More Complicated Function

Shallower
Less Complicated Function

Yoshua Bengio, Learning Deep Architectures for AI, Foundations and Trends in Machine Learning, 2(1), 2009

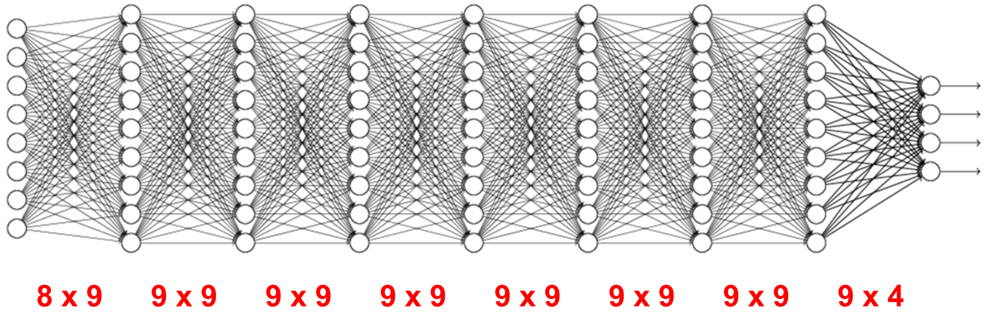
What's New?

- DNN is less accurate than shallow one by using traditional backpropagation
  - Backpropagation loses its power in deep architecture
  - Vanishing gradient problem



What's New?

- DNN is less accurate than shallow one by using traditional backpropagation
  - Optimization is very complex
  - Too many parameters in deep architecture

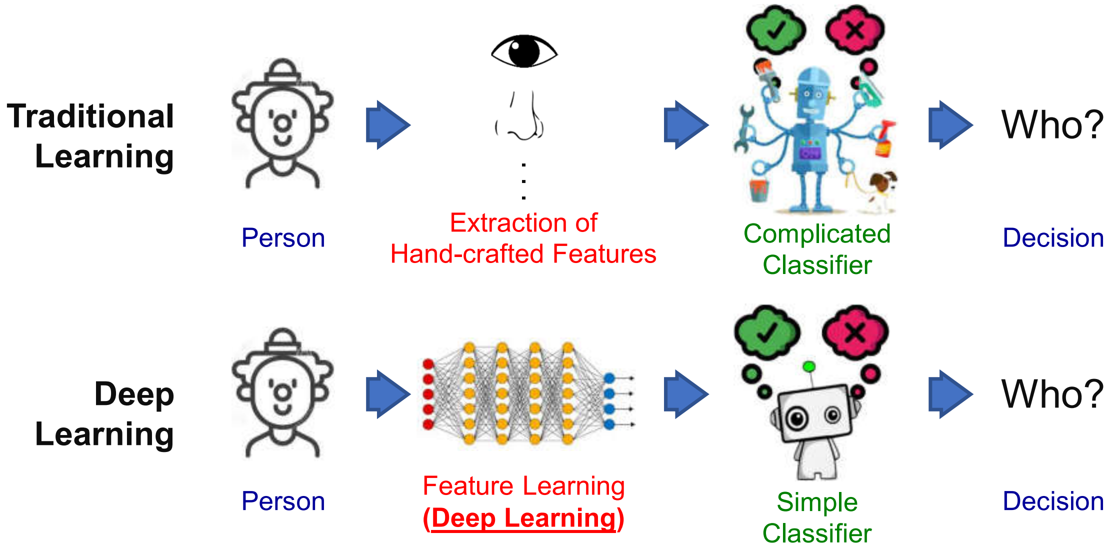


What's New?

- Vanishing Gradient Problem
  - **Divide and Conquer**
    - Stacked training
    - E.g. Stacked Autoencoder (SA)
  - **Reduce Parameters**
    - Too many parameters
    - E.g. Convolutional Neural Network (CNN)

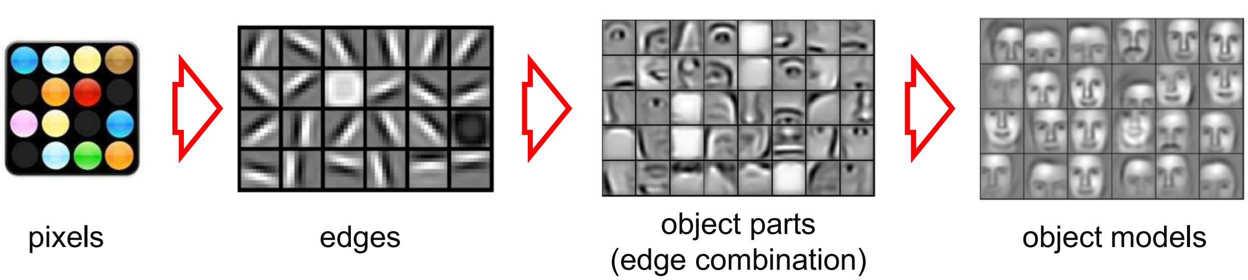
Feature Learning

- Deep Learning **focuses on feature learning** but not a classifier



Feature Learning

- Features extracted by deep learning



Other Machine Learning Types

- **Regression**
  - A statistical modeling technique used to predict continuous variables based on the relationship between independent and dependent variables.
- **Multi-label classification** (**Tagging**)
  - A classification problem where an instance can be assigned multiple labels simultaneously, allowing for more flexible and nuanced categorization.
- **Recommendation**
  - A system or algorithm that suggests items, products, or content to users based on their preferences, behaviors, or similarities to other users.
- **Reinforcement Learning**
  - A branch of machine learning where an agent learns to make decisions or take actions in an environment to maximize a reward signal, often through trial and error.

Classifier Comparison

- For a classification problem, given
  - Dataset D
  - Classifiers A and B

- How can we measure which classifier, A or B, is better for D?

Classifier Comparison

- Method
  - Randomly separate D into **training** and **test sets**
  - Use **Training Set** to train A and B
  - Use **Test Set** to evaluate the performances of trained A and B
  - Select the better performing classifier

- **Is it ok?**
  - The winner may just be lucky in performing better for that particular test set.
  - No guarantee for different test sets

Classifier Comparison

- The bias of test set should be reduced
- Two re-sampling techniques
  - Independent Run
  - Cross-Validation

Classifier Comparison

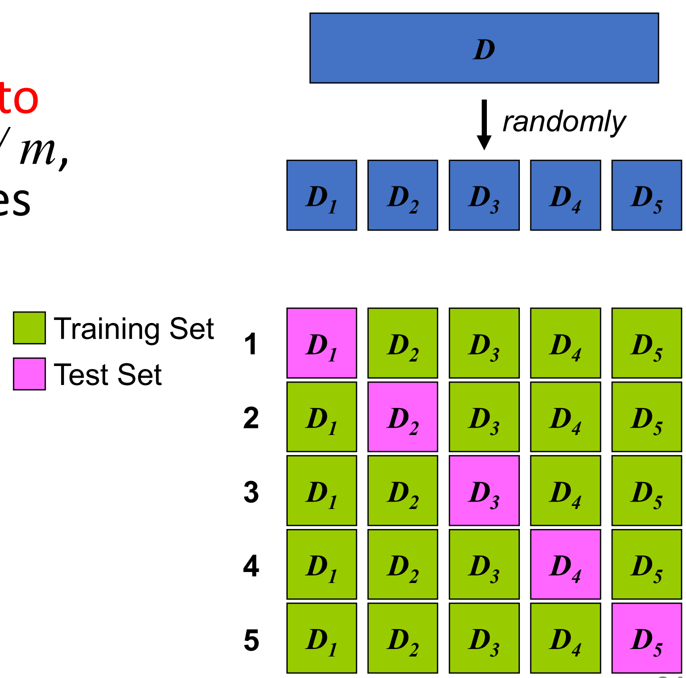
Independent Run

- Statistical method
- Also called Bootstrap and Jackknifing
- Repeat the experiment "n" times independently
  - Repeat n times
    - i is the number of running time
    - Randomly separate D into Training Set$_i$ and Test Set$_i$
    - Use Training Set$_i$ to train A_i and B_i
    - Use Test Set$_i$ to evaluate the trained A_i and B_i
  - Select the classifier with higher average accuracy

Classifier Comparison

Cross-Validation

- M-fold Cross-Validation
- Dataset D is randomly divided into m disjoint sets D_i of equal size n / m, where n is the number of samples in dataset
- Repeat m times
  - Trained by D_j
  - Evaluated by all D_i except D_j
- Select the classifier with higher average accuracy



Machine Learning
Terminology

- **Instance / Sample**
  Observations from an application

- **Feature / Attribute**
  Property or characteristic of a sample

- **Dimensionality**
  The number of features

Machine Learning
Terminology

- **Training Set**
  A set of samples used to train a model

- **Test Set**
  A set of samples used to evaluate the performance of the trained model.
  Usually separate from the training set.

- **Unseen Samples**
  Any samples not in training set

Machine Learning
Terminology

- **Training Error**

  Error on training samples

- **Test Error**

  Error on test samples

- **Generalization Error**

  The ability of a model to perform well on unseen samples

  In some discussion,

  Test Error = Generalization Error

Machine Learning
Terminology

- **Objective Function / Error Function / Loss Function**

  A mathematical function used to quantify error made by a model, closely related to the objective

  Can be more than error on samples, may include any other concepts

  E.g. complexity of a model